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GENDER AND BANKING: ARE WOMEN BETTER LOAN OFFICERS?

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Gender and Banking:

Are Women Better Loan Officers?

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Abstract

We analyze gender differences associated with loan officer performance. Using a unique data set for a commercial bank in Albania over the period 1996 to 2006, we find that loans screened and monitored by female loan officers show statistically and economically significant lower default rates than loans handled by male loan officers. This effect comes in addition to a lower default rate of female borrowers and cannot be explained by sample selection, overconfidence of male loan officers or experience differences between female and male loan officers. Our results seem to be driven by differences in monitoring, as loan officers of different gender do not seem to screen borrowers differently based on observable borrower characteristics. This suggests that gender indeed matters in banking.

JEL Classification: G21; J16
Keywords: Behavioral banking, loan officers; gender; loan default; monitoring; screening

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1. Introduction

Does gender matter in banking? While the role of gender has been explored in a variety of fields in finance, such as investment decisions, mutual fund management, equity analyst performance or corporate financial decisions, and the behavior and importance of loan officers in financial institutions has been studied in several recent papers, the impact of loan officers' gender on loan default risk has not been analyzed, yet. This paper uses a unique loan-level data set for an Albanian bank over the period 1996 to 2006 to assess the relationship between borrowers' and loan officers' gender and the probability of loan default, controlling for a vast array of borrower, loan and loan officer characteristics. Specifically, controlling for the borrowers' gender, we test whether male or female loan officers experience a lower default probability on "their" loans.

Understanding the role of gender in banking is interesting and important for practitioners and researchers alike. For instance, designing incentives for loan officers to minimize loan losses might have to take into account loan officers' gender if empirical findings point to differences between male and female loan officers in their screening and monitoring abilities. Exploring the relationship between loan officers' gender and loan default risk also adds to the literature on borrower-loan officer relationships. In fact, recent studies point to the existence of such behavioral divergences. For instance, Agarwal and Wang (2008) show theoretically and empirically that the choice of effort made by loan officers depends on the compensation scheme implemented by the bank, the information asymmetry between the loan officer and the bank, and the loan officer's career concerns. Hertzberg et al. (Forthcoming) show empirically that loan officers are more likely to reveal negative information in the case of job rotation because it seems to be better if the loan officer reveals this kind of negative information herself instead of having bad information being revealed by a successor loan officer.

Theory and intuition provide ambiguous predictions of how the gender of the loan officer might be related to the default probability of their borrowers. For instance, Bharat et al. (2009) argue that male executives have better access to private information, which in the case of loan officers could result in a superior performance of male loan officers. Further, consider that in patriarchic societies male loan officers might have a stronger standing vis-à-vis borrowers, be they male or female, in terms of monitoring and disciplining them, thus ensuring loan repayment. Hence, we would observe a lower default probability of loans screened and monitored by male loan officers. On the other hand, several studies have shown that women are more risk averse than men in their investment decisions (e.g. Charness and Gneezy, 2007; Christiansen et al., 2006[1]). Thus, it may be that loans handled by female loan officers are less likely to default because women grant loans more restrictively. Other studies (e.g. Barber and Odean, 2001) argue that men are more overconfident than women. With respect to loan officer performance this could result in male loan officers screening and monitoring more loans than would be optimal, eventually leading to an inferior performance compared to female loan officers. Another hypothesis in favor of a superior performance of female loan officers is that female loan officers have typically fewer outside options in the labor market and have therefore stronger incentives to excel in form of low default rates in their loan portfolio.[2] Yet another competing hypothesis is that loan officers might have an easier time monitoring and disciplining borrowers of their own gender, hence, we would expect to find a lower default probability of female borrowers if the loan is approved and monitored by a female rather than by a male loan officer, with the reverse

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[1] More general works on differences in risk-aversion between male and female decision makers are Barsky et al. (1997) and Agnew et al. (2003). Croson and Gneezy (2009) provide an excellent overview over the literature on differences in risk aversion between women and men and other reasons for gender differences.

[2] Darity and Mason (1998) provide a comprehensive overview of gender discrimination in the labor market.

holding for male loan officers.[3] Given the ambiguity of theoretical predictions, it is an empirical question whether men or women are better loan officers and whether this effect varies with the gender of the borrower.

While the role of gender has not been explored in the context of banking, it has been analyzed in a variety of other fields in financial economics, such as investment decisions, equity analyst performance, corporate executives' behavior, corporate financial decisions, and mutual fund management. The evidence on performance differences between women and men is mixed in this literature. On the one hand, Barber and Odean (2001) find evidence that female investors seem to be less overconfident and, thus, trade less frequently. This leads to a superior performance of female investors. In addition, Levi et al. (2008) show that in the case of female CEOs, the bid premium over the pre-announcement target share price is much smaller than compared to M&A deals with male counterparts. On the other hand, Green et al. (2008) analyze the performance of male versus female Wall Street equity analysts and document that male analysts seem to have better forecasting abilities, i.e. women seem to perform worse at hard, quantifiable tasks. Bharat et al. (2009) find that male senior executives are more successful in insider trading than their female peers. They argue that the reason for this finding is that female executives have a disadvantage vis-à-vis males in accessing inside information. Finally, Huang and Kisgen (2009) analyze whether men and women differ in corporate financial decisions. They find that acquisitions made by female CFO firms have significantly higher announcement returns and argue that women appear to undertake greater scrutiny and exhibit less hubris in acquisition decisions. Additionally, female CFOs issue debt less frequently, and debt and equity issuances are associated with higher announcement returns.

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[3] This hypothesis is related to the cultural affinity literature (Cornell and Welch, 1996; Bostic, 2003).

Our paper makes a contribution to two burgeoning strands of literature. First, it contributes to the increasing number of behavioral banking studies in which the impact of gender has so far not been addressed.[4] Second, it contributes to the studies in financial economics that have analyzed the importance of decision makers' gender in other contexts but banking. By analyzing the impact of loan officers' gender on loan default risk our paper thus adds a new facet to the behavioral banking literature. To the best of our knowledge, no other study has analyzed, yet, whether gender matters in banking. By exploring the effect of gender on loan officer performance, this study is the first to provide evidence on the importance of gender in banking.

For our analyses, we use a loan-level data set including more than 43,000 loan applications provided by a commercial bank serving individual borrowers and small and medium-sized firms in Albania. For each loan, we can identify the loan officer who screened the borrower and subsequently monitored her over the lifetime of the loan. A possible default of the loan can thus be directly linked to a specific loan officer. The data set also includes extensive information about borrower characteristics such as the gender or the marital status of the borrower, loan characteristics such as size, maturity and interest rate of the loan, and loan officer characteristics such as gender and experience within the institution. One particularly advantageous feature of our data set is that it comprises information on rejected applicants, which enables us to explicitly test for sample selection and screening differences between female and male loan officers.

We find that borrowers screened and monitored by female loan officers have significantly lower default rates than male loan officers. This result holds for both female and male borrowers and is robust to controlling for borrower's gender and for the correlation between borrower's and

[4] While Agarwal and Wang (2008) control for the gender of the loan officer in the regression analysis, they do not focus on these results.

loan officer's gender. Besides the statistical significance, the performance difference is also economically significant, as in our baseline analysis female loan officers have default rates for female and male borrowers which are, in absolute terms, roughly 4.5 percent lower than the default rates of male loan officers. Our findings hence suggest that not only the institutional design of financial institutions matters, but also the gender of the people operating in it. This is a novel result in the literature.[5]

We also explore possible explanations for this performance advantage of female loan officers. First, we find that female loan officers are not assigned to less risky borrowers. Second, controlling for a vast array of borrower characteristics, we cannot find any difference between female and male loan officers in their acceptance of applicants. This enables us also to rule out that female loan officers grant loans more restrictively compared with male loan officers based on observable borrower characteristics. Third, we do not detect any differences in the workload of male vis-à-vis female loan officers. If male loan officers had a significantly higher workload, this might be an indication of overconfidence of male loan officers (Barber and Odean, 2001). Fourth, our results do not vary with different experience levels of female and male loan officers.[6] In addition, we find that female loan officers are significantly younger than male loan officers when they start working for the bank, which can be explained by compulsory military service for men in Albania. Both findings indicate that the educational background of female and male loan officers is not significantly different.

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[5] See also Berger et al. (2005), Mian (2006), and Liberti and Mian (Forthcoming) on the importance of financial institutions' design. Agarwal and Wang (2008) also find a lower default rate for female than for male loan officer, but do not explore or discuss this finding in their study.

[6] Experience might be negatively related to loan default risk if loan officers gain expertise on screening and monitoring borrowers over time (Andersson, 2004).

Our results are thus not consistent with the result of Bharat et al. (2009) who argue that males have easier access to inside information as in this case we would expect male loan officers to have lower default rates. Our results also do not support the hypothesis that loan officers are more successful in handling loans from borrowers with the same gender, as might be suggested by the cultural affinity literature. Our findings rather indicate that female loan officers are more successful in monitoring borrowers – regardless of the gender of the borrower – but also might be better in screening based on unobservable applicant characteristics. This result is consistent with the view that female loan officers face stronger performance incentives because of the higher dependence on the existing job due to labor market discrimination and their lower mobility. It is also consistent with the finding from other fields that women are more risk-averse.

The remainder of the paper is organized as follows. Section 2 discusses the data and section 3 the methodology. Section 4 presents our main results and several robustness checks. Section 5 explores several possible explanations for the performance differences between female and male loan officers. Section 6 concludes.

2. Data

We use a unique data set of both rejected and accepted loan applicants from a commercial lender serving individuals and small- and medium-sized enterprises (SMEs) in Albania. Specifically, we have information on over 43,000 loan applications and 31,000 loans given by the lender over the period January 1996 to December 2006. In addition, our data set contains information on 203 loan officers and covers five branches of the bank in the Albanian capital, Tirana. The lender grants mainly loans for business, real estate, and consumption purposes. While it clearly focuses on the low-income and small-enterprise segment, financial sustainability and therefore profitability is the primary goal.

Table 1 provides some basic data about the bank. Specifically, it shows for the 11 years of our sample period the number of loan applications, number of approved loans, average loan size, borrower characteristics, loan usage, and the share of loans handled by female loan officers. The bank grew substantially over the past 11 years, from originally 350 loans in 1996 to over 7,000 loans in 2006. Over this period, the approval ratio, defined as the number of approved applications divided by the number of all applications, increased strongly, from 44 percent in 1996 over 60 percent in 2000 to 71 percent in 2006, which can be partly explained by the increasing share of repeat borrowers. The average loan size was 4,258 US dollars, illustrating that the loan portfolio of the bank consists mainly of small individual loans and loans to SME.[7] While the bank initially focused on loans for business purposes, in 2006 already 30 percent were for consumption purposes.

We define a loan as being in default if at least one of a borrower's payments was in arrears for more than 30 days at any point over the whole lifetime of the loan.[8] The default rate varied significantly over the sample period, from a high of 24.5 percent for loans granted in the first year to a low of 1.4 percent in 2006, most likely reflecting an increase in experience of the lender and a higher share of repeat loans.[9] The share of loans by female borrowers is low, with, on average, only 22 percent, though slightly increasing over the last years of the sample period, to 24 percent in 2006. The share of loans handled by female loan officers, on the other hand, is high with an average of 57 percent of loans being handled by female loan officers. This share, however, has been decreasing over time, dropping to 52 percent in 2006.

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[7] However, it is noteworthy that the GDP per capita in Albania is significantly lower than in highly developed countries, thus the small absolute loan size might be misleading.

[8] For robustness we also use time periods of 15, 60, and 90 days in the empirical analyses.

[9] Note that the default frequency is not the yearly default frequency, but rather the default frequency of all loans being granted in 1996, 1997, and so on. Therefore, the low default frequency in the last year is partly due to the effect of loans still outstanding at the end of our sample period.

For our regression analyses, we restrict and cut the data in several ways. For the main analysis, we restrict our attention to actual borrowers and their default behavior and thus drop unsuccessful loan applicants. Second, we focus on a set of borrowers that have had only one loan with the bank, for several reasons. The first reason is that the database we use is constructed in a way that all socio-demographic borrower data are overwritten whenever a new loan application is submitted by a customer that had already applied for a loan before. Hence, some of the socio-demographic data we use as control variables might not be up to date if we use also further loan applications by the same borrower.[10] The second reason is that the comparison of first (and at the same time last) loan applications allows for a consistent comparison as all loan officers have the same limited information about the respective borrower at the time of the application.[11] In the case of repeat borrowers, loan officers already have historic information, which they can take into consideration when granting and monitoring the loan. Focusing on the first loan by each successful loan applicant thus allows us to study in a clean way gender-specific loan officer performance differences. Third, we drop loans with missing gender information on the borrower or the loan officer level. For that purpose, we exclude loans by borrowers classified as corporate clients in the database because in these cases we cannot observe the borrowers' gender information. Fourth, we drop loans with amounts of less than 100 US dollars and more than US 100,000 dollars. While very low values might result from false entries in the database we want to exclude very large loans that do not fit the definition of small individual and SME loans. In addition, we exclude loans with an unreasonable borrower age (younger than 18 or older than 75

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[10] For instance, a certain customer might have applied for a loan in 1996 when she was not married and again in 2000 when she was married. As the data we use were provided by the lender in January 2007, the database would classify that particular customer as being married also in 1996, although in 1996 this was not the case.

[11] This rests on the reasonable assumption that loan applicants and loan officers did not know each other before the loan application was forwarded.

years). Finally, we exclude loans approved in December 2006 as we cannot observe these loans' performance.[12] This reduces our sample from 31,000 to 6,775 loans granted by 141 loan officers for the baseline regression analysis. In robustness tests we use a different cut of the data and obtain samples containing more than 14,000 loans. Combining all analyses with different data cuts we use over 30,000 loan applications.

We include a vast array of borrower, loan officer and loan characteristics in the regression of loan defaults. Table 2 presents descriptive statistics and correlations for these variables. Specifically, in addition to controlling for the borrower's gender, we control for her civil status, employment status (self-employed or salaried employee) and age. We expect female, married and employed borrowers to be less likely to default, because of higher opportunity costs of defaulting and more stable incomes. We also include the number of persons in the borrower's household, whether there is a phone available, and whether the borrower lives in or outside Tirana. While the availability of a phone might increase the ease of monitoring by the loan officers and therewith reduce default risk, there is no clear a-priori relationship between household size and default probability. On the other hand we expect borrowers living outside of Tirana and thus farther away from the nearest branch to have a higher default risk (DeYoung et al., 2008).

The descriptive statistics in Table 2A indicate that, on average, 23.1 percent of the loans in our sample are given to female borrowers, while 57.7 percent are approved by female loan officers. These numbers are similar to the ones presented in Table 1 and indicate that the data selection process did not induce a strong sample bias. On average, borrowers are 39 years old, 75.4 percent of borrowers are married, while 12.4 percent are self-employed. On average, there

[12] The overwhelming majority of the loans have an installment frequency of one month. As the data covers the period until December 31, 2006, it is impossible for a borrower who was given a loan in December 2006 to default on her loan until the end of our sample period.

are almost five persons in a borrower's household, there is a phone available in 93.2 percent of borrowers' households, and 79 percent of the borrowers live in Tirana.

The correlations in Panel B of Table 2 show that female, older, and married borrowers, borrowers with a phone, and borrowers living in Tirana face a lower default probability, while household size and employment status are not significantly correlated with default probability. In addition, there are many significant correlations among borrower characteristics. For example, female borrowers are less likely to be married or self-employed and live in smaller households.

We also control for several loan characteristics that might affect a loan's default probability. Specifically, we control for the annualized interest rate, the approved amount and the adjusted maturity of the loan.[13] Further, we include the ratio of approved to applied loan amount and the type of collateral (personal, mortgage, or chattel guarantee) provided.[14] Higher interest rates can result in adverse selection of borrowers with riskier projects and in riskier behavior of borrowers (Stiglitz and Weiss, 1981). Similarly, a lower approved share might signal higher default risk, while longer-term loans tend to be riskier. On the other hand, there is a-priori no clear relationship between collateral type or loan purpose and default risk. The descriptive statistics in Table 2A show that annualized interest rates varied between 4.3 and 24.1 percent, with an average of 13.8 percent. Female loan officers charge interest rates which are 70 basis points lower compared with their male peers. The average loan size is 3,729 US dollars, while the loan maturity varies between 1 month and 6 years, with an average of 16 months. Again, female loan officers provide usually larger loans (4,083 versus 3,247 US dollars) and loans with longer maturities (517 versus 450 days). On average, borrowers received 88.8 percent of the amount

[13] Some loans in the database mature after 2006. These loans' maturity was adjusted to December 31, 2006 in order to be able to compare the outstanding loans with already matured loans.
[14] The use of chattel guarantees is quite common in countries like Albania as objects from the household of a borrower (such as a fridge or a television) often have very high (not necessarily monetary) values for the borrowers.

they applied for.[15] 96.2 percent of all loans were secured with chattel collateral, while 12.4 percent provided mortgages and 15.0 percent personal guarantees.

The correlations in Panel B of Table 2 show that longer-term loans, loans with higher interest rates and loans that are smaller relative to the amount originally applied for are more likely to default, while loan size is not significantly correlated with default probability. Loans with a personal guarantee are more likely to default, while other guarantees are not significantly correlated with default probability. Larger and longer-term loans, loans with personal and mortgage guarantees carry lower interest rates. Some of the loan characteristics are also correlated with borrower characteristics. Female borrowers, for example, pay lower interest rates and are less likely to default.

Finally, we control for several loan officer characteristics. Specifically, in addition to the gender of loan officers, we include their age and the number of loan applications they have processed since they started working for the bank. The correlation of age and experience with default probability is ex ante not clear. While age and experience might improve loan officers' performance (Andersson, 2004), the career concern view discussed in Agarwal and Wang (2008) would predict the opposite relationship, as younger loan officers care more about their career. The age of loan officers in our sample ranges from 19 to 32 years, with an average of 25 years. Female loan officers were on average 24 years old while their male peers were 2 years older. On average, loan officers have processed already 223 loan applications. In addition, we find huge differences in their experience because the number of already processed loans ranges from 1 to over 1,000 loans. The correlations in Table 2B indicate that female loan officers are, on average,

[15] We winsorize the approved share at the 1st and 99th percentile to account for outliers.

younger, while they do not have more experience in terms of loan applications processed. Older analysts have processed more loan applications.

There are significant differences between female and male loan officers in terms of borrower characteristics and loan conditions, although some of these differences are statistically, but not economically significant (Table 2A and 2B). Female loan officers are more likely to process loan applications of female, younger, non-married, and not self-employed borrowers. Critically, we find that loans granted by female loan officers have significantly lower default rates than male loan officers, 12 percent vs. 15.7 percent. If we compare the gender-gender combinations of borrowers and loan officers, we find that female loan officers have an average default rate for female borrowers of 7.8 compared with 11.5 percent for male loan officers. For male borrowers, on the other hand, the default rate of female loan officers is 13.5 percent compared with 16.6 percent for male loan officers. We next explore whether these performance differences remain when controlling for other loan officer and borrower as well as loan characteristics in a multivariate setting.

3. Methodology

We use two main baseline specifications to disentangle the relationship between loan default probability and the gender of borrowers and loan officers. Specifically, for the first set of results we utilize a binary probit model of the following form:

$$Default_i = \alpha + \beta_1 * Female_i + \beta_2 * Female\ loan\ officer_j + \gamma * D_i + \delta * X_j + \varepsilon_i \qquad (1)$$

where $Default_i$ is a binary variable taking the value 1 if customer i defaulted on her loan (i.e. was in arrears for at least 30 days once during the lifetime of the loan), $Female_i$ is a dummy variable taking the value 1 for female borrowers, $Female\ loan\ officer_j$ is a dummy variable taking the value 1 if the loan officer j serving borrower i is female, D_i is a vector of control variables referring to borrower and loan i, X_j is a vector of control variables referring to loan officer j and ε is an error term. In addition, we include dummies for the five branches of the lender to control for potential clustering of loan officers of a certain gender or ability in a specific branch, year dummies to control for macroeconomic factors that might affect default risk of borrowers, and five business sector dummies (construction, production, other services, trade, transport) to control for risk differences associated with the business sector the borrower operates in. Results for these additional controls will be omitted from the tables. Standard errors are clustered at the loan officer level, thus allowing for unobserved correlation between loans processed and monitored by the same loan officer (Froot, 1989).[16]

Given that loan officers may have superior screening or monitoring capabilities for borrowers of the same gender, our second set of baseline results utilizes several interaction terms to disentangle the relationship between default probability and gender pairs of borrower and loan officer:

$$\begin{aligned}&Default_i = \alpha + \beta_1 * Female_i * Female\ loan\ officer_j + \beta_2 Male_i * Female\ loan\ officer_j + \\ &\beta_3 Male_i * Male\ loan\ officer_j + \gamma * D_i + \delta * X_j + \varepsilon_i\end{aligned} \qquad (2)$$

where the combination female borrower-male loan officer is the omitted category. The coefficient β_1 thus indicates whether female borrowers are more or less likely to default with a female than with a male loan officer, while the difference between β_2 and β_3 indicates whether male borrowers are more or less likely to default with a female than with a male loan officer. This specification therefore allows us to not only control for the correlation between borrower and loan officer gender, but also to distinguish between the performance difference of female and

[16] As suggested by Petersen (Forthcoming) we also reproduced all reported and unreported results by using heteroskedasticity robust standard errors without accounting for cluster correlation (White, 1980). The results are significant at similar or even higher statistical levels. They are available upon request.

male loan officers among borrowers of different genders. In order to draw conclusions about the economic as well as the statistical significance of our results, we only present marginal coefficient estimates that are computed at the sample mean.

4. Main results

This section reports and discusses our main findings, using the two regression models described above, and testing the robustness of our results to different samples and specifications.

4.1. Baseline regressions

The results in Column 1 of Table 3 suggest that female borrowers and borrowers served by female loan officers are less risky. The default probability of female borrowers is 3.9 percent lower than that of male borrowers across our sample of first (and last) loans. We also find that the default probability of borrowers served by female loan officers is 4.5 percent lower than the default probability of borrowers served by male loan officers. Both effects are economically significant, as the average default rate in our sample is 13.5 percent.[17] On the other hand, the default probability does not vary with the experience of the loan officer. The number of loan applications the loan officer has already processed, one of our proxies for a loan officer's experience, does not enter significantly.[18]

Several other loan officer, borrower and loan characteristics enter significantly in the column 1 regression of Table 3. First, older borrowers and borrowers served by older loan officers are less likely to default. The latter result contradicts the career concern hypothesis by Agarwal and Wang (2008). Second, consistent with Stiglitz and Weiss (1981), the interest rate is positively, significantly, and economically very substantially associated with a higher default

[17] Note that all results we report are marginal effects, that is, the differences are absolute changes.
[18] We divide the number of loan applications per loan officer by 1,000 for scaling reasons.

probability. Third, married borrowers and borrowers from households where a phone is available are less likely to default, suggesting higher opportunity costs for these borrowers. Fourth, borrowers living outside Tirana are more likely to default, confirming the results obtained by DeYoung et al. (2008) who analyzed U.S. data and found that borrowers living farer away from the bank are more likely to default. Fifth, larger loans and loans with longer maturities are more likely to turn non-performing. Sixth, the higher the ratio of approved to applied loan amount, the lower is the default probability. Finally, loans with personal guarantees are more likely to turn bad, while loans guaranteed with mortgages are less likely to default. An explanation for this finding may be that personal guarantees, which are third-party guarantees, induce a moral hazard, while the potential loss of own property sets strong repayment incentives. Overall, the fit of our model is satisfactory, with 74 percent of the defaulted loans and 62 percent of the non-defaulted loans predicted correctly[19] and an adjusted McFadden R-square of 11.5 percent.

The results in Column 2 of Table 3 show that the performance advantage of female loan officers is robust to controlling for the correlation between loan officer and borrower gender and holds for both female and male borrowers. Since the finding that female loan officers experience lower default rates might be driven by the fact that female borrowers are less risky than male borrowers and are more likely to be screened and monitored by female loan officers, we construct borrower gender-loan officer gender combinations as dummy variables and run a regression using specification (2). Compared to female borrowers monitored by male loan officers, female borrowers monitored by female loan officers have a default probability that is 4.6 percent lower. Similarly, in Panel B we find that the default probability of male borrowers monitored by female

[19] In classifying observations, predicted probabilities significantly higher than 13.5 percent (average default probability) are classified as default observations and those below 13.5 percent are classified as no default. We adjust this cut off value depending on the sample and default (approval) definition.

loan officers is 4.5 percent lower than the default probability of male borrowers monitored by male loan officers. Both results are statistically and economically highly significant suggesting that, independent of the gender of the borrower, female loan officers are better in managing default risk. Our previous findings on the different loan officer, loan and borrower characteristics are confirmed by this regression.

Columns 3 to 5 of Table 3 demonstrate the robustness of our results to using alternative default definitions. Specifically, we redefine default as having a payment in arrears for more than 15 days (column 3), 60 days (column 4) and 90 days (column 5). Our findings are all confirmed for the stricter default definition of 15 days. Here we also find that the advantage of female loan officers vis-à-vis their male peers is stronger for female borrowers (6.3 percent) than for male borrowers (4.6 percent). In the case of less strict definitions (columns 4 and 5), the size of the marginal effect of loan officer's gender for female borrower declines but stays significant, while the effect of loan officer's gender turns insignificant for male borrowers.

Finally, in column 6 of Table 3 we confirm our findings for a larger sample of first loans for which we also have information on subsequent loan applications. Here, we do not restrict our attention to the first loans that were at the same time the last loans by the borrowers, but we use all first loans available in the database. As in this case we cannot be sure that the socio-demographic information has not changed after the first loan, we exclude all socio-demographic variables from the regression. This less strict cut of the data leaves us with a sample containing 14,020 first loans. The column 6 results of Table 3 show that even when using this larger sample, we confirm our finding that female loan officers are more efficient in preventing a loan default than their male peers.[20] While the marginal effects are somewhat smaller in size, we still find that female loan officers are better in preventing loan defaults than their male peers, both for female and for male borrowers. The results for the other controls are very similar to our previous regressions. The overall fit of the model decreases, as can be seen from the adjusted McFadden R-square and the percentage of correctly predicted default observations, underlining the importance of the socio-demographic borrower characteristics in predicting default.

4.2. Robustness tests

We next present and discuss the results of a series of additional tests to illustrate the robustness of our findings from the baseline regressions. First, we loosen the strict sample selection that we had chosen for our baseline regression. Specifically, we expand the sample from first loans to borrowers' repeat loans. This allows us a robustness test in two directions: first, we can use a different sample, and, second, we expect a less significant relationship between the gender of the loan officer and default probability as the information asymmetries and thus agency problems between bank and borrower should be lower in the case of a repeat loan. We also test for this directly by including a variable indicating the duration of the borrower's relationship with the bank and by interacting this variable with the borrower-loan officer gender pairs.[21] As shown by Mester et al. (2007) historic borrower information can substantially improve a bank's monitoring success. Hence, for this robustness check we include several control variables that capture a borrower's loan history with the bank. Specifically, we control for the duration of the lending relationship in years, whether any previous loan application of the borrower has been

[20] For this regression we use the 30 days in arrears default definition. In unreported regressions we confirm our earlier findings using this bigger sample without socio-demographic data for the alternative default definitions of 15, 60, and 90 days.

[21] Duration is measured here as the time between the first loan application and the loan application in the sample of repeat loans by the respective borrower in days.

rejected and whether the borrower has ever defaulted on any loan granted by the lender before applying for a new loan. As in the baseline regression, we first focus on a sample of last loans to be able to control for socio-demographic borrower characteristics. Cutting the data in this way leaves us with 6,448 repeat loans. Note that this sample is entirely different from the sample used in the baseline regression as the latter only included first loans.

The results in Panel A, column 1 of Table 4 confirm the previous findings and their interpretation with a regression using repeat instead of first loans. We continue to find that female borrowers screened and monitored by female loan officers have a lower default probability than if screened and monitored by male loan officers, while, on the other hand, there is no significant difference for male borrowers anymore. However, even in the case of female borrowers, the economic significance is substantially smaller than before, with only 1.8 percent, compared to the 4.6 percent we found in column 2 of Table 3. The column 2 regression of Table 4 shows that this performance gap is not a function of how long the borrower has been borrowing from the institution because the interaction terms between the borrower-loan officer gender pairs and the duration of the lending relationship do not enter significantly. Large proportions of the explanatory power seem to shift to the loan history data, consistent with Mester et al. (2007). Specifically, we find that defaults are on average 37.1 (3.7) percent more likely if the same borrower defaulted on a previous loan (had a rejected loan application before).

The results in columns 3 and 4 of Table 4 confirm these findings for a larger sample of 12,940 repeat loans that is not limited to last loans. As before, we do not use the socio-demographic borrower characteristics for these regressions. The column 3 results without the interaction term show that the performance advantage of female vis-à-vis male loan officers is now only 1.6 percent for female borrowers. For male repeat borrowers the advantage is 1.0 percent, but only weakly significant, at the 10 percent level. The size of the performance gap for female repeat borrowers in column 4 remains, but loses significance, and the marginal effect for male borrowers does not enter significantly either. Again, we do not find that the performance gap is a function of the duration of borrowers' lending relationship with the bank. We further find that focusing on repeat loans and including loan history variables increases the fit of the model considerably, as can be seen from the higher adjusted McFadden R-square and percentages of correctly predicted defaults.[22]

Taken together, the results in Table 4 suggest that the performance advantage of female vis-à-vis male loan officers continues to hold for repeat loans, although robustly so only in the case of female borrowers. Critically, however, we find that this effect is smaller for repeat loans compared with first loans, while it is not a function of the duration of borrowers' relationship with the bank. It thus seems that the learning effect that reduces the performance advantage of female loan officers vis-à-vis their male counterparts kicks in with the second loan.

Second, we use a two-step Heckman procedure (Heckman, 1976; 1979) to account for potential sample selection bias that might result from the screening process, as so far we have used only the approved loan applications.[23] A unique feature of our data set is, however, that it includes information about approved as well as rejected loan applications. Hence, for this robustness test, we use all loan applications (rejected as well as approved) that were at the same time first and last loan applications. This yields a sample of 9,885 loan applications. Heckman's selection equation therefore uses the loan approval decision (approval = 1 if the loan was granted)

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[22] In unreported regressions, we combine first and subsequent loans by the same borrower and estimate specification (2) for the combined sample, including a variable indicating the number of the approved loan by each borrower. In the first case, we focus only on the last loans in order to be able to use the socio-demographic data, and in the second case we use all approved loans in the sample without including socio-demographic data. For both samples, we continue to find that female loan officers have statistically and economically significantly lower default rates than male loan officers for female as well as for male borrowers.

[23] Another potential sample selection might occur at the beginning of the loan application process when the loan applicant is assigned to her loan officer. We analyze this (ex ante) sample selection bias in section 5.1.

as dependent variable. Other than that, we use a very similar regression set up as in column 2 of Table 3, with the only notable differences that we cannot use the interest rate because it was not available at the time of the application, and that we use the applied rather than the approved amount as well as the applied instead of the approved maturity. Heckman's second equation, the loan default regression with selection-bias corrected coefficients, follows specification (2) and includes 6,775 approved loans. We find that the coefficient of the inverse Mills ratio is not significant, indicating that our results from the baseline regression do not suffer from sample selection.[24]

Third, instead of using the default occurrence as dependent variable, we employ a proxy for the realized loss the bank is suffering from its loan defaults. The intuition behind this robustness test is that while female loan officers have lower default rates, it might be that their defaults are more severe, i.e., that the bank loses more money when the borrower of a female loan officer defaults. As we do not have data on the exact amounts the bank loses from the loan defaults in our data set, we construct a proxy for the realized loss by multiplying the default occurrence with the loan amount given to the respective borrower.[25] As our correlation analysis showed that female loan officers give higher loan amounts than their male colleagues, this might reduce the female performance advantage we have found earlier. We then use this realized loss proxy as our dependent variable, with the explanatory variables being the same as the ones used in column 2 of Table 3 apart from the approved amount which we have to exclude from our set of explanatory variables. As the dependent variable in this regression is a continuous variable rather

[24] As the Heckprobit (Heckman approach for a probit regression) maximum-likelihood estimation with our binary dependent variable does no converge, we use the described two-step linear probability model with bootstrapped standard errors. With regard to the exclusion restrictions, we tried several reasonable variables and our results did not change. We omit reporting these results to save space, they are available upon request.

[25] This approach assumes that the loss given default (LGD) equals 100 percent and that the borrowers default immediately after the loan was granted.

than being binary and given that our sample exhibits strong overdispersion (the variance of the dependent variable is much larger than the mean), we use a generalized linear estimation technique (GLM) assuming a negative binomial distribution. The estimation results show that the loan officer effect we found for the default rate is confirmed for the realized loss proxy, both in terms of statistical and economical significance.[26]

All in all, these results illustrate the robustness of our results, which hold over different samples, are robust to the use of a different performance measure, and do not seem to suffer from screening-induced sample selection bias.

5. The gender performance gap – exploring the mechanisms

The results reported in the previous section suggest a robust performance advantage of female loan officers, especially in the case of female borrowers. This section explores four possible mechanisms that can explain this finding. Specifically, we test whether female loan officers get assigned different clients than their male colleagues, are better at screening, might have more experience or have a lower work load.

5.1. Ex ante sample selection bias

One possible explanation for our finding that female loan officers have lower default rates than male loan officers may be that they simply have better clients, i.e., that there is an ex ante selection bias. This type of selection bias differs from the sample selection bias discussed in the previous section, which can be accounted for by using the described Heckman correction. The selection bias we will explore in this section would happen even before screening when applicants are assigned to loan officers.

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[26] Results are available upon request.

The first best solution to capture an ex ante selection bias would be to conduct a random experiment which allows considering observable as well as unobservable borrower characteristics that might drive loan outcomes.[27] In the absence of such a possibility, we analyze the approved as well as the rejected loan applications to test whether there is an ex ante selection bias based on observable borrower characteristics.[28] Specifically, we estimate the following regression model:

$$Female\ loan\ officer_i = \alpha + \gamma * D_i + \varepsilon_i \qquad (3)$$

with the loan officer gender dummy as dependent variable and the explanatory variables we used in specification (2) apart from the gender-interaction dummies and the variables that are not available for rejected loans (such as the interest rate).[29] The sample consists of 9,885 first and at the same time last loan applications of which 7,695 (77.8 percent) were approved.[30] We estimate regression model (3) separately for the 7,483 male and the 2,352 female loan applicants in this sample. We also re-run the default regression of column 2 in Table 3 separately for male and female borrowers and compare the signs from those regressions with the signs of significant coefficients in specification (3) to see whether female loan officers are more likely to get assigned riskier applicants.

The results in Table 5 suggest that there is no selection bias stemming from the assignment of applicants to female or male loan officers. The column 1 results show that male applicants who live in Tirana and male applicants applying for bigger loan amounts are more

[27] Such experiments have become quite popular among economists. See, for instance, Bertrand et al. (Forthcoming) and Karlan and Zinman (Forthcoming) with an application to credit markets.
[28] We acknowledge, however, that the problem of ex ante selection bias based on unobservable borrower characteristics is not solved by using this approach.
[29] We also exclude the maturity as otherwise we lose a high number of observations from the pool of rejected loan applications. Results are invariant to this.
[30] The difference between these 7,695 approved first loans and the smaller sample we use in the baseline regression is simply due to the non-availability of data for some of the independent variables included in the Table 3 regressions, which we did not include in the Table 5 regressions.

likely to be served by a female loan officer, and male borrowers having a personal guarantee as collateral are less likely to be served by female loan officers. As we find that male borrowers who live outside Tirana are less likely to default (column 3), this suggests that, with regard to this borrower characteristic only, female loan officers have ex ante the less risky male applicants (indicated in column 5 of Table 5). There is thus relatively little evidence that female loan officers face significantly less risky male clients and that this drives their superior ex post performance.

Running the same regression for female applicants, we find four significant effects; female loan officers seem to serve younger female clients, fewer female applicants with access to a phone, female clients with bigger loan requests, and more female applicants with a chattel mortgage. Since we find that bigger loans tend to default more often, this suggests that male loan officers seem to serve the less risky female clients. Any superior performance of female loan officers for female borrowers does, therefore, not seem to be driven by ex ante selection bias. On the contrary, this analysis shows that female loan officers should even have a more difficult job in managing the default risk of female clients, thus, making their superior performance vis-à-vis male loan officers even more striking.

5.2. Screening

The superior performance of female loan officers may be attributable to their better screening capacities. For instance, if female loan officers are better in screening their borrowers, then they will have a better pool of clients after loan approval takes place. This, in turn, could explain their lower default rates. Alternatively, female loan officers might simply be more restrictive because of their higher degree of risk-aversion (e.g. Barber and Odean, 2001; Christiansen et al., 2006; Charness and Gneezy, 2007). If this were true, we would expect that controlling for other borrower characteristics, female loan officers should be more likely to reject borrowers. To test whether differences in screening drive our results we use a sample containing both approved and rejected loan applications and run the following regression

$$Approval_i = \alpha + \beta_1 * Female_i * Female\ loan\ officer_j + \beta_2 Male_i * Female\ loan\ officer_j + \beta_3 Male_i * Male\ loan\ officer_j + \gamma * D_i + \delta * X_j + \varepsilon_i \tag{4}$$

where $Approval_i$ is a dummy variable that indicates whether a loan application was approved or not. In contrast to specification (2) we are not able to use some loan-related control variables, such as the interest rate and, rather than using the approved loan amount as a loan size proxy, we use the applied loan amount.[31]

We test for screening differences using four different samples. First, we use a sample of first loan applications, which at the same time were the last applications, thus corresponding to the specification of Table 3 (columns 1 to 5), with 9,885 loan applicants, around 78 percent of which were accepted.[32] Second, we drop the socio-demographic variables and include all first loan applications, yielding a sample of 17,882 loan applications. Third, we use a sample of repeat borrowers. Again, we run a specification with loan applications that were at the same time last loan applications (sample size of 8,073 loan applications) and a specification without this restriction and, thus, without socio-demographic borrower characteristics (15,874 loan applications).

The results in Table 6 illustrate that our finding of a superior performance of female vis-à-vis male loan officers is not driven by better screening capacities of female loan officers based on observable borrower characteristics. We do not find any significant difference in the likelihood of borrowers to be accepted by female or male loan officers, independent of whether

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[31] The maturity variable is again excluded from the analysis as it would considerably reduce our sample size. Results are invariant to this.
[32] Here we also include loans approved in December 2006, unlike for the arrears regressions.

the borrower is male or female, except the Table 6, column 4 results in Panel B where we find that male loan officers are more likely to accept further loan applications of male clients. In unreported robustness tests, we do not find any significant difference in the ratio of approved to applied loan amount nor in the ratio of approved to applied maturity between male and female loan officers, suggesting that female loan officers are not more risk averse in their approval decisions based on observable borrower characteristics.[33] When using interest rates as dependent variable, we find that loans screened by female loan officers carry a 31 basis points higher interest rate in the case of female borrowers, while there is not significant different for male borrowers.[34] Overall, these results suggest that screening differences between female and male loan officers do not drive the performance gap between them.[35]

We also separately analyzed the pool of rejected loan applications to test whether female loan officers reject riskier customers. Given that only 22 percent of all applications are rejected, a better screening ability might remain unobserved in the previous test with all loan applications because approved loans dominate the sample. The results of the separate analysis of rejected loans, which are available upon request, do not indicate any better screening capacity of female loan officers. We conclude from these analyses that the superior performance of female loan officers do not seem to be attributable to their better screening capacities, at least not based on observable characteristics; this does not exclude that female loan officers are better at the smell test, i.e. rejecting risky applicants based on unobservable characteristics, a point to which we will return later.

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[33] Results are available on request.
[34] While it is a loan committee rather than the loan officer who sets the interest rate, this interest rate might reflect the riskiness of the borrower.
[35] This result matches the finding by Agarwal and Wang (2008) who do not find any significant difference in acceptance decisions between male and female loan officers for a borrower sample from a U.S. bank.

5.3. Loan officer experience and education

While the previous two tests focus on ex ante selection bias and better screening capacity of female loan officers, we now test whether the better performance of female loan officers is based on higher experience. For that purpose we add to specification (2) interaction terms between the borrower-loan officer dummy of interest and a variable proxying for the loan officer's experience. Specifically, we control for loan officer experience by interacting the borrower-loan officer gender with two experience dummies indicating low respectively high experience

$$
\begin{aligned}
&Default_i = \alpha + \beta_{1,k} * Female_i * Female\ loan\ officer_j * Experience_{k,j} + \\
&\beta_{2,k} Male_i * Female\ loan\ officer_j * Experience_{k,j} + \\
&\beta_{3,k} Male_i * Male\ loan\ officer_j * Experience_{k,j} + \gamma * D_i + \delta * X_j + \varepsilon_i
\end{aligned} \tag{5}
$$

where k denotes low (below the median) or high (above the median) experience. This regression specification yields seven borrower's gender-loan officer's gender-loan officer's experience interaction terms, the omitted category being the combination female borrower-male loan officer with low (or high) experience. The experience proxies we use are (i) the number of loan applications already handled by the loan officer, (ii) the number of years the loan officer has worked for the bank, and (iii) the loan officer's age. The sign and significance of the coefficient $\beta_{1,1}$ ($\beta_{1,2}$) indicate whether female loan officers with low (high) experience have lower default rates for female borrowers than male loan officers of the same experience level. If experience differences drive the superior performance of female loan officers, we expect to find a significant effect only for experience levels above the median (i.e. $\beta_{1,2}$). As in specification (2) we also test for differences between female and male loan officers serving male borrowers by using the male borrower-male loan officer-low (high) experience reference category. Table 7 contains the results of these regressions.[36]

In Panel A of Table 7, the column 1 regression shows that the advantage of female loan officers in managing the default risk of female borrowers holds for low as well as for high experience. The sizes of the marginal effects are similar to our previous finding from column 2 of Table 3. In Panel B, however, we see that female loan officers are better than male loan officers in managing default risk of male borrowers only for high levels of experience.

Column 2 presents the results when using the time since the loan officer works for the bank as experience proxy.[37] The use of this alternative experience proxy shows that the performance difference for female borrowers exists only for a low level of experience. The magnitude of the effect is stronger than before. We further find that the performance gap with regard to male borrowers exists for low as well as high loan officer experience.

Finally, column 3 presents the results when using loan officer age as experience proxy. The performance of female loan officers with regard to female borrowers is better for low as well as high levels of experience, while for male borrowers, we again find performance differences only for a high experience level. All in all, the superior performance of female loan officers varies only very little with experience, especially in the case of female borrowers. We can thus conclude that differences in experience are not the main driver of our results.[38]

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[36] Note that the two marginal effects for the borrower's gender-loan officer's gender-experience combination for female and male borrowers represent the results of two separate regressions, the first being the regression where the respective omitted category is the one with low experience and the second the one with high experience.
[37] We do not use this variable in the other specifications because it is highly correlated with our first experience proxy, the *Loan applications per loan officer* variable.
[38] Our results are also not driven by a higher share of female loan officers working for a longer time in the bank, as there is no significant difference in overall time with the bank between male and female loan officers.

A closely related potential explanation of our results could be that the average female loan officer has a higher level of education than the average male loan officer, and is, hence, more capable of serving her customers, eventually leading to performance advantages. As has been argued in the literature, women seem to be discriminated in labor markets.[39] Hence, we could hypothesize that they need to have a higher average level of education in order to be employed by the bank rather than otherwise comparable men with a lower level of education. While we do not have explicit information about the educational background of the loan officers working for the bank, we use the age of female and male loan officers when they start working for the bank as a proxy for education. For instance, if female loan officers were considerably older than male loan officers when they start working for the bank, this could indicate a higher level of education because they simply had more time for their education.

We proxy the time at which the respective loan officer started working for the bank by using the age of female and male loan officers at the time they handled their first loan application. We find that female loan officers are on average 21 years and 10 months old, compared to an average age of 23 years and 2 months of male loan officers. The age difference is significant at the 1 percent level using a t-test, suggesting that women do not spend more time for their education before they start working for the bank.[40] While this comparison is not a stringent test for educational differences between female and male loan officers, it provides at least tentative evidence that female loan officers do not appear to be better educated on average than male loan officers.

[39] See, e.g., Ashenfelter and Hannan (1986) on gender related labor market discrimination in the banking industry.
[40] Men are subject to mandatory military service in Albania, which might explain why men are significantly older than women when they start working for the bank.

All in all, we conclude from these tests that the superior performance of female loan officers is neither driven by their higher experience nor their better education.

5.4. Differences in workload

Differences in workload of female vis-à-vis male loan officers may also explain the superior performance of female loan officers. For instance, if male loan officers worked significantly more than female loan officers, this might reduce the monitoring intensity per borrower and, eventually, the monitoring success of male loan officers. We may think of two reasons why male loan officers work more than female loan officers. First, it may be a decision of the bank to assign more loan applications and therewith, given that the approval ratios are not different between male and female loan officers, more borrowers to male loan officers. Second, male loan officers may volunteer to handle more loan applications, as sign of a higher degree of overconfidence of male loan officers as previously documented in the literature (e.g. Lewellen et al., 1977; Barber and Odean, 2001; Agnew et al., 2003).

To test for differences in workload between male and female loan officers we first calculate the number of loan applications handled by either loan officer type separately for different time intervals. For instance, we compare how many loan applications male loan officers handled in their first year with the bank with the number of loan applications handled by female loan officers in their first year. Then, we do the comparison for the first two years, three years, etc. The time intervals are constructed by using the dates on which the respective loan officer handled the first and the last loan application.[41] This allows us to approximate the time the respective loan officer has worked for the bank. We then count the number of loan applications handled over this time horizon and do a standard t-test for differences. We do this separately for

[41] We neither know the exact date when the loan officer started working for the bank nor her last working day.

all loan applications received, i.e., all screened and monitored loans, as well as for all approved loans, i.e., only monitored loans. We focus on the 141 loan officers included in our sample for the baseline regression. With regard to the loan applications, however, we do not exclude any loan application because of missing data for the independent variables. Hence, these tests are based on all loan applications included in the database.

The results in Table 8 show that although male loan officers tend to have a slightly higher workload, none of the differences is statistically significant at conventional levels. Hence, the difference in monitoring success that we detected does not seem to be driven by female loan officers having fewer borrowers to monitor.

6. Conclusions

This study is, to the best of our knowledge, the first to consider the role of gender in banking by analyzing loan officer performance differences. It contributes to the burgeoning literature on behavioral banking as well as to the literature on gender differences in financial economics. Our main finding is that gender indeed seems to matter in banking: female loan officers have statistically and economically significantly lower default rates associated with their borrowers. This novel result holds for both female and male borrowers, with the effect being more pronounced for female borrowers.

Our analyses also shed light on the mechanisms as we can rule out several obvious explanations for our finding. First, we demonstrate that ex ante selection bias arising from the assignment of borrowers to specific loan officers does not seem to drive our findings. Second, we do not find evidence that female loan officers have better screening abilities, based on observable borrower characteristics. Third, potential differences in experience and educational backgrounds of female and male loan officers do not seem to drive our results. Finally, we can rule out that male loan officers work significantly more than female loan officers and have, hence, less time to monitor their borrowers.

All in all, our results suggest two possible explanations of why loans handled by female loan officers are less likely to default; first, they are better in screening based on unobservable borrower characteristics and, second, they are better in monitoring their borrowers. While we cannot distinguish between the two, we esteem that the effect is more likely to come through better monitoring than through better screening, for the following reason. Female loan officers accept the same percentage of applicants as male loan officers and their loans do not show any significant differences in other loan terms, such as the approved to applied ratio or approved to applied maturity and almost no difference in interest rates. In order for better screening on unobserved borrower characteristics to explain differences in default probabilities, female loan officers have to be better in avoiding both type I and type II errors to the same extent, i.e. for each marginal borrower they reject but that would have been accepted by a male loan officer, they would have to accept a marginal borrower that would have been rejected by a male loan officer.

While novel results, our findings are subject to some caveats. The ideal way to test the effect of gender on loan officer performance would be through a randomized experiment. Such randomization would have to take place along two dimensions: on the decision to become loan officer and the assignment of applicants to loan officers. While the latter is certainly feasible, the former seems impossible to undertake in the real world as one cannot randomly choose individuals from the overall population to work as loan officers for a bank. In our analysis, we try to establish that our findings are not biased due to the non-random nature of the data. Unlike in a randomized experiment, however, we are left with the possibility that the performance gap between male and female loan officers is driven by unobservable borrower characteristics that female loan officers are better in distinguishing. In addition, we cannot exclude the possibility that female loan officers differ from their male colleagues along dimensions that we are not able to capture. Future research should focus on these issues and further explore the mechanisms and channels through which the different incentives of female and male loan officers work. We also hope that our research can be replicated for other institutions and countries.

References

Agarwal, S., Wang, F.H., 2008, Motivating Loan Officers: An Analysis of Salaries and Piece Rates Compensation, Working Paper, Federal Reserve Bank of Chicago.

Agnew, J., Balduzzi, P., Sundén, A., 2003, Portfolio Choice and Trading in a Large 401(k) Plan, American Economic Review 93, 193-215.

Andersson, P., 2004, Does Experience Matter in Lending? A Process-tracing Study on Experienced Loan Officers' and Novices' Decision Behavior, Journal of Economic Psychology 25, 471-492.

Ashenfelter, O., Hannan, T., 1986, Sex Discrimination and Product Market Competition: The Case of the Banking Industry, Quarterly Journal of Economics 101, 149-174.

Barber, B.M, Odean, T., 2001, Boys Will Be Boys: Gender, Overconfidence, and Common Stock Investment, Quarterly Journal of Economics 116, 261-292.

Barsky, R.B., Juster, F.T., Kimball, M.S., Shapiro, M.D., 1997, Preference Parameters and Behavioral Heterogeneity: An Experimental Approach in the Health and Retirement Study, Quarterly Journal of Economics 112, 537-579.

Berger, A.N., Miller, M., Petersen, M., Rajan, R., Stein, J., 2005, Does Function Follow Organizational Form? Evidence from the Lending Practices of Large and Small Banks, Journal of Financial Economics 76, 237-269.

Bertrand, M., Karlan, D., Mullainathan, S., Shafir, E., Zinman, J., Forthcoming, What’s Advertising Content Worth? A Field Experiment in Consumer Credit Market, Quarterly Journal of Economics.

Bharath, S.T., Narayanan, M.P., Seyhun, H.N., 2009, Are Women Executives Disadvantaged?, Working Paper.

Bostic, R.W., 2003, A Test of Cultural Affinity in Home Mortgage Lending, Journal of Financial Services Research 23, 89-112.

Charness, G., Gneezy, U., 2007, Strong Evidence for Gender Differences in Investment, Working Paper.

Christiansen, C., Schröter Joensen, J., Rangvid, J., 2006, Gender, Marriage, and the Decision to Invest in Stocks and Bonds: Do Single Women Invest More in Less Risky Assets?, Working Paper.

Cornell, B., Welch, I., 1996, Culture, Information, and Screening Discrimination, Journal of Political Economy 104, 542-571.

Croson, R., Gneezy, U., 2009, Gender Differences in Preferences, Journal of Economic Literature 47(2), 448-474.

Darity Jr., W.A., Mason, P.L., 1998, Evidence on Discrimination in Employment: Codes of Color, Codes of Gender, Journal of Economic Perspectives 12, 63-90.

DeYoung, R., Glennon, D., Nigro, P., 2008, Borrower-lender Distance, Credit Scoring, and Loan Performance: Evidence from Informational-opaque Small Business Borrowers, Journal of Financial Intermediation 17, 113-143.

Froot, K.A., 1989, Consistent Covariance Matrix Estimation with Cross-Sectional Dependence and Heteroskedasticity in Financial Data, Journal of Financial and Quantitative Analysis 24, 333-355.

Green, C. T., Jegadeesh, N., Tang, Y., 2008, Gender and Job Performance: Evidence from Wall Street, NBER Working Paper No. 12897.

Heckman, J., 1976, The Common Structure of Statistical Models of Truncation, Sample Selection and Limited Dependent Variables, Annals of Economic and Social Measurement 5, 475-492.

Heckman, J., 1979, Sample Selection Bias as a Specification Error, Econometrica 47, 153-161.

Hertzberg, A., Liberti, J.M., Paravisini, D., Forthcoming, Information and Incentives Inside the Firm: Evidence from Loan Officer Rotation, Journal of Finance.

Huang, J., Kisgen, D., 2009, Gender and Corporate Finance, Working Paper, Boston University.

Karlan, D., Zinman, J., Forthcoming, Observing Unobservables: Identifying Information Asymmetries with a Consumer Credit Field Experiment, Econometrica.

Levi, M.D., Li, K., Zhang, F., 2008, Mergers and Acquisitions: The Role of Gender, Working Paper.

Lewellen, W. G., Lease, R.C., Schlarbaum, G.G., 1977, Patterns of Investment Strategy and Behavior Among Individual Investors, Journal of Business 50, 296-333.

Liberti, J.M., Mian, A., Forthcoming, Estimating the Impact of Hierarchies on Information Use, Review of Financial Studies.

Mester, L.J., Nakamura, L.I., Renault, M., 2007, Transactions Accounts and Loan Monitoring, Review of Financial Studies 20, 529-556.

Mian, A., 2006, Distance Constraints: The Limits of Foreign Lending in Poor Economies, Journal of Finance 61, 1465-1505.

Petersen, M., Forthcoming, Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches, Review of Financial Studies.

Stiglitz, J.E., Weiss, A.M., 1981, Credit Rationing in Markets with Imperfect Information, American Economic Review 71, 393-410.

White, H., 1980, A Heteroskedasticity-Consistent Covariance Matrix and a Direct Test for Heteroskedasticity, Econometrica 48, 817-838.

Table 1: Development of the lending institution

This table contains a broad overview for the five Tirana branches of the Albanian bank that provided the data. The loan size is given in US dollars and the default frequency is measured as the occurrence of a borrower being in arrears for more than 30 days during the lifetime of her loan. It is not the yearly default frequency, but rather the default frequency of all loans being granted in 1996, 1997, and so on. Business loans incorporate investments into fixed assets and working capital. Real estate loan usages include the purchase, construction, improvement and extension of houses.

					Loan usage			Share of loans	Share of loans
Year of application	Applications	Approved Loans	Loan Size	Default frequency	Business loans	Real estate	Consuming	by female borrowers	by female loan officers
1996	794	351	3,646	0.245	1.000	0.000	0.000	0.165	0.645
1997	454	251	3,348	0.080	1.000	0.000	0.000	0.164	0.684
1998	934	482	4,615	0.085	1.000	0.000	0.000	0.135	0.793
1999	1,064	597	5,368	0.034	0.845	0.155	0.000	0.175	0.866
2000	2,416	1,463	4,112	0.103	0.676	0.323	0.001	0.174	0.660
2001	2,258	1,482	3,743	0.063	0.649	0.348	0.004	0.194	0.674
2002	2,552	1,963	5,826	0.058	0.545	0.393	0.062	0.176	0.754
2003	3,791	2,993	6,445	0.049	0.443	0.320	0.237	0.207	0.673
2004	9,724	7,894	4,084	0.108	0.399	0.289	0.312	0.237	0.541
2005	9,515	7,365	4,091	0.098	0.597	0.164	0.239	0.209	0.463
2006	9,976	7,040	3,447	0.014	0.595	0.094	0.300	0.242	0.522
Sum	43,478	31,881							
Average			4,258	0.075	0.569	0.213	0.215	0.216	0.568

Table 2A: Descriptive statistics

This table contains borrower, loan, and loan officer characteristics for a sub sample of 6,775 approved loans used in the baseline analysis. The table concentrates on the first and last loans for each borrower. We further drop loans with unreasonable entries for the borrower's age (smaller than 18 or larger than 75 years), missing gender information for borrower and loan officer, and applied loan size (smaller than 100 or larger than 100,000 US dollars). The first four columns show results for all observations used in the baseline analysis while column five and six split the sample with respect to loans approved by female respectively male loan officers. Column six shows also t-test results for mean differences between female and male officers; *,**,*** indicate significance at the 10%, 5% and 1% level, respectively. *Female* is a dummy variable indicating the gender of the borrower (female = 1), *Female loan officer* is a dummy variable indicating the gender of the loan officer (female = 1), *Age of borrower* is the age of the borrower at the time of the loan application, *Civil status* is a dummy variable indicating whether the borrower is married (married = 1), *Self employed* is a dummy variable indicating whether the borrower is self-employed or a wage earner, *Number persons household* indicates how many persons including the borrower are in the household of the borrower, *Phone availability* is a dummy variable indicating whether the borrower has a phone or not (phone available = 1), *Borrower lives in Tirana* is a dummy variable indicating whether the borrower lives in or outside Tirana (in Tirana = 1), *Approved amount* is the loan size granted in US dollars, *Adjusted maturity* is the loan maturity in days adjusted such that no loan has a maturity greater than December 31, 2006, *Interest rate* is the annual interest rate charged on the loan, *Approved share* is the ratio of applied amount to approved amount in percent, *Personal guarantee, Mortgage guarantee, and Chattel guarantee* are all dummy variables indicating whether any of the three respective types of collateral are pledged by the borrower, *Applications per loan officer* is a loan officer experience proxy indicating the number of loan applications handled by the loan officer until the respective loan was granted, *Age of loan officer* is the age of the loan officer at the time the loan was granted measured in years.

	All observations (n = 6,775)				Female loan officer (n = 3,909)	Male loan officer (n = 2,866)
Variable	Mean	Minimum	Median	Maximum	Mean	Mean
Default	0.135				0.120	0.157***
Female borrower	0.231				0.270	0.177***
Female loan officer	0.577					
Age of borrower	39	18	38	74	39	40***
Civil status	0.754				0.710	0.813***
Self employed	0.124				0.045	0.232***
Number persons household	4.825	1	5	21	4.655	5.057***
Phone availability	0.932				0.931	0.932
Borrower lives in Tirana	0.790				0.872	0.678***
Approved amount	3,729	140	2,322	100,000	4,083	3,247***
Adjusted maturity	488	31	450	2,060	517	450***
Interest rate	0.138	0.043	0.148	0.241	0.135	0.142***
Approved share	0.888	0.300	1.000	1.333	0.900	0.871
Personal guarantee	0.150				0.163	0.132***
Mortgage guarantee	0.124				0.149	0.090***
Chattel guarantee	0.962				0.951	0.977***
Applications per loan officer	223	1	163	1090	226	219
Loan officer age	25	19	24	32	24	26***

Table 2B: Correlation matrix

This table contains the pair-wise correlations for borrower, loan, and loan officer characteristics for a sub sample of 6,775 approved loans used in the baseline analysis. Refer to Table 2A for a description of the variables and the sample selection. * indicates a significance level of at least the 5% level.

	Default	Female	Female loan Officer	Applications per loan officer	Loan officer age	Interest rate	Age of borrower	Civil status	Self employed	Household size	Phone availability	Borrower lives in Tirana	Approved amount	Adjusted maturity	Approved share	Personal guarantee	Mortgage guarantee
Female	-0.073*																
Female loan officer	-0.053*	0.110*															
Applications per loan officer	-0.067*	0.050*	0.017														
Loan officer age	-0.055*	-0.013	-0.348*	0.277*													
Interest rate	0.102*	-0.060*	-0.126*	0.041*	0.000												
Age of borrower	-0.076*	-0.007	-0.058*	-0.031*	0.017	-0.043*											
Civil status	-0.050*	-0.122*	-0.118*	-0.068*	0.008	-0.020	0.487*										
Self employed	-0.017	-0.059*	-0.281*	0.086*	0.226*	0.083*	0.028*	0.073*									
Household size	-0.014	-0.155*	-0.114*	-0.011	0.025*	0.063*	0.142*	0.320*	0.082*								
Phone availability	-0.110*	0.010	-0.003	0.093*	0.066*	-0.068*	-0.042*	-0.055*	0.056*	0.007							
Borrower lives in Tirana	-0.072*	0.194*	0.236*	0.032*	-0.066*	-0.112*	-0.047*	-0.162*	-0.189*	-0.251*	0.057*						
Approved amount	-0.011	0.008	0.071*	-0.123*	-0.041*	-0.448*	0.048*	0.058*	-0.020	-0.010	0.032*	0.053*					
Adjusted maturity	0.055*	-0.009	0.126*	-0.411*	-0.197*	-0.289*	0.048*	0.044*	-0.180*	-0.055*	0.008	0.092*	0.430*				
Approved share	-0.059*	0.054*	0.076*	-0.015	-0.007	-0.122*	-0.025*	-0.081*	0.006	-0.101*	0.087*	0.107*	0.110*	0.163*			
Personal guarantee	0.049*	-0.025*	0.043*	-0.235*	-0.095*	-0.257*	0.014	0.048*	-0.149*	0.030*	-0.122*	-0.022	0.196*	0.344*	0.012		
Mortgage guarantee	-0.010	-0.018	0.089*	-0.207*	-0.078*	-0.420*	0.075*	0.081*	-0.095*	-0.030*	-0.118*	0.024	0.568*	0.503*	-0.002	0.298*	
Chattel guarantee	0.019	-0.004	-0.067*	0.119*	0.063*	0.177*	-0.040*	-0.027*	0.065*	0.075*	0.112*	-0.054*	-0.218*	-0.293*	0.007	-0.160*	-0.485*

Table 3: Default probability and loan officers' gender – first loans

This table contains the marginal effects of the outcome test with the gender of borrowers and loan officers. The first five regression models are based on sub samples of approved loans that are at the same time first and last loans per borrower. Regression model VI comprises all 14,020 first loans and does not contain socio-demographic variables. For regression models I, II, and VI, the dependent variable is the occurrence of a borrower being in arrears for more than 30 days during the lifetime of her loan. Regression models III, IV, and V use arrear definitions of 15, 60, and 90 days, respectively. The independent variables are as described in Table 2A except the number of loan applications per borrower which is divided by 1,000. In addition, instead of the raw numbers we employ the natural logarithm for the approved amount (*ln(approved amount))* and the adjusted maturity (*ln(adjusted maturity))*. In regression models II to VI, we interact the borrower and loan officer gender: *Female & Female loan officer* is a dummy variable indicating the combination of a female borrower and a female loan officer, *Male & Female loan officer* indicates the combination of a male borrower and a female loan officer, *Male & Male loan officer* indicates the combination of a male borrower and a male loan officer. We also control for five loan destinations (working capital, fixed assets, mixed purpose, real estate, and consumption), five business sectors (construction, production, trade, transport, other services), five branches, and the years from 1996-2006. Results for these control variables are omitted. In Panel A, the combination *Female & Male loan officer* serves as the reference group, in Panel B, the combination *Male & Male loan officer* serves as the reference group. Standard errors are clustered at the loan officer level. All results remain if we use Huber-White standard errors instead. *,**,*** indicate significance at the 10%, 5% and 1% level, respectively.

	Marginal effects for regression model					
Independent variable	I	II	III	IV	V	VI
Panel A: Reference group is Female & Male loan officer						
Female	-0.039***					
Female loan officer	-0.045***					
Female & Female loan officer		-0.046***	-0.063***	-0.035***	-0.038***	-0.023**
Male & Female loan officer		-0.008	-0.014	-0.006	-0.012	-0.004
Male & Male loan officer		0.033**	0.029*	0.008	-0.004	0.027***
Loan applications per loan officer	0.019	0.020	0.032	-0.023	-0.029	0.013
Age of loan officer	-0.008***	-0.008***	-0.01***	-0.004**	-0.003*	-0.005***
Interest rate	0.841***	0.841***	1.018***	0.365***	0.275**	0.559***
Age of borrower	-0.002***	-0.002***	-0.002***	-0.001***	-0.001***	-0.001***
Civil status	-0.034***	-0.034***	-0.050***	-0.008	-0.003	
Self employed	0.014	0.014	0.032	0.012	0.015	
Number persons household	-0.003	-0.003	-0.005**	-0.003*	-0.002*	
Phone availability	-0.084***	-0.084***	-0.119***	-0.035***	-0.032***	
Borrower lives in Tirana	-0.042***	-0.043***	-0.063***	-0.019**	-0.018***	
ln(approved amount)	0.018**	0.018**	0.015*	0.023***	0.017***	0.015**
ln(adjusted maturity)	0.029**	0.029**	0.057***	0.000	0.001	0.050***
Approved share	-0.104***	-0.104***	-0.119***	-0.074***	-0.058***	-0.043***
Personal guarantee	0.023*	0.023*	0.031**	0.004	0.007	0.014*
Mortgage guarantee	-0.032**	-0.032**	-0.043***	-0.033***	-0.025***	-0.014
Chattel guarantee	0.015	0.015	0.014	0.008	0.008	0.018

(Table 3 continued)

Independent variable	Marginal effects for regression model I	II	III	IV	V	VI
Panel B: Reference group is Male & Male loan officer						
Male & Female loan officer		-0.045***	-0.046***	-0.015	-0.009	-0.031***
Observations	6,775	6,775	7,107	6,670	6,571	14,020
Adjusted McFadden R-square	0.115	0.115	0.134	0.120	0.126	0.081
Share of default correctly predicted	74.1	73.9	76.5	76.5	77.1	71.3
Share of non-default correctly predicted	61.8	61.9	60.9	63.2	66.1	62.0

Table 4: Default probability and loan officers' gender – repeat loans

This table contains the marginal effects of the outcome test with the gender of borrowers and loan officers together with interactions with the duration of the lending relationship. Regression models I and II (III and IV) are based on the sub sample of 6,448 repeat and last (12,940 repeat) loans. The dependent variable is the occurrence of a borrower being in arrears for more than 30 days during the lifetime of her loan. The independent variables are as in Table 3 except for three variables for the loan history of each borrower with the bank: *Duration relationship* provides the number of years since the first loan application of the borrower, *Any previous application rejected* is a dummy variable indicating any previous rejection of a loan application (1 = rejection), *Any previous loan defaulted* is a dummy variable indicating any previous default (1 = default). We further use three interaction terms between the borrower gender-loan officer gender pairs and *Duration relationship* in regression models II and IV. Results for our additional control variables are omitted. In Panel A, the combination *Female & Male loan officer* serves as the reference group, in Panel B, the combination *Male & Male loan officer* serves as the reference group. Standard errors are clustered at the loan officer level. All results remain if we use Huber-White standard errors instead. *,**,*** indicate significance at the 10%, 5% and 1% level, respectively.

	Marginal effects for regression model			
Independent variable	I	II	III	IV
Panel A: Reference group is Female & Male loan officer				
Female & Female loan officer	-0.018**	-0.020*	-0.016**	-0.016
Male & Female loan officer	-0.004	-0.007	-0.007	0.000
Male & Male loan officer	0.004	-0.006	0.003	0.007
Female & Female loan officer & Duration relationship		0.007		0.002
Male & Female loan officer & Duration relationship		0.001		-0.004
Male & Male loan officer & Duration relationship		0.005		-0.002
Duration relationship	-0.008***	-0.009***	-0.007***	-0.005*
Any previous application rejected	0.037***	0.036***	0.027***	0.027***
Any previous loan defaulted	0.371***	0.374***	0.298***	0.297***
Loan applications per loan officer	0.001	0.000	0.001	0.001
Age of loan officer	-0.002	-0.002	-0.001	-0.001
Interest rate	0.230**	0.228**	0.270***	0.268***
Age of borrower	-0.001***	-0.001***	-0.001***	-0.001***
Civil status	-0.017**	-0.017**		
Self employed	0.011	0.011		
Number persons household	0.001	0.001		
Phone availability	-0.033**	-0.033***		
Borrower lives in Tirana	0.002	0.002		
ln(approved amount)	0.005	0.005	0.009***	0.009***
ln(adjusted maturity)	0.032***	0.032***	0.044***	0.044***
Approved share	-0.036***	-0.036***	-0.027***	-0.026***
Personal guarantee	0.000	0.000	0.008	0.009
Mortgage guarantee	-0.022***	-0.022***	-0.011*	-0.010*
Chattel guarantee	0.015	0.015	0.010	0.011
Panel B: Reference group is Male & Male loan officer				
Male & Female loan officer	-0.008	-0.004	-0.010*	-0.010
Male & Female loan officer & Duration relationship		0.003		0.001
Observations	6,448	6,448	12,940	12,940
Adjusted McFadden R-square	0.249	0.248	0.159	0.158
Share of default correctly predicted	84.9	84.8	75.2	75.1
Share of non-default correctly predicted	70.5	70.7	67.2	67.2

Table 5: Test for ex ante sample selection

This table contains the marginal effects of the test for ex ante sample selection using first and at the same time last loan applications. We thus add rejected loan applications to the baseline sample of approved loans. We estimate two separate regressions with 7,483 applications by male and 2,352 applications by female customers. The dependent variable is whether the loan officer handling the loan application is a male or a female loan officer (female loan officer = 1, otherwise zero). The independent variables are as in Table 3 except for the gender dummies, the approved amount which is substituted by the applied amount, and the approved maturity which is not used because it would considerably reduce the sample sizes (results remain if the variable is used). Results for our additional control variables are omitted. Column 3 (4) of the table indicates whether the respective variable has an ex post significant risk reducing (-) or risk increasing effect (+) according to the results of the outcome regressions in Table 3 when we split the sample into one containing male and another including only female borrowers. Column 5 (6) indicates for male (female) borrowers whether the respective result of column 1 (2) is in favour of female (male) loan officers. Standard errors are clustered at the loan officer level. All results remain if we use Huber-White standard errors instead. *,**,*** indicate significance at the 10%, 5% and 1% level, respectively.

	Borrower gender		Male borrower	Female borrower	Male borrower	Female borrower
Independent variable	Male	Female	Risk effect		In favor of	
Age of borrower	-0.001	-0.002*	-			
Civil status	-0.032	0.031	-	-		
Self employed	-0.069	-0.015				
Number persons household	0.000	0.008				
Phone availability	-0.035	-0.090**	-			
Borrower lives in Tirana	0.084***	0.008	-		Female loan officer	
Applied amount	0.045***	0.050**		+		Male loan officer
Personal guarantee	-0.043*	-0.015				
Mortgage guarantee	0.058	0.056	-			
Chattel guarantee	0.075	0.132**				
Observations	7,483	2,352				
Adjusted McFadden R-square	0.193	0.141				

Table 6: Test for differences in screening

This table contains the marginal effects for a test whether female and male loan officers experience differences in their screening abilities. The regression models are based on different sub samples of loan applications: model I is based on 9,885 loan applications that are at the same time first and last applications per borrower; model II uses 17,882 first loan applications; model III employs 8,073 loan applications that are at the same time further and last applications per borrower; model IV is based on 15,874 further loan applications. The dependent variable is the approval decision (1 for an approved loan, 0 otherwise). We use a different set of control variables because we cannot use variables that are not available at the time of the loan application, such as the interest rate. Specifically, we employ the natural logarithm of the applied instead of the approved loan amount, and the natural logarithm of the applied instead of the approved maturity. All other control variables are as in Tables 3 and 4. Results for some of these control variables are omitted. In Panel A, the combination *Female & Male loan officer* serves as the reference group, in Panel B, the combination *Male & Male loan officer* serves as the reference group. Standard errors are clustered at the loan officer level. All results remain if we use Huber-White standard errors instead. *,**,*** indicate significance at the 10%, 5% and 1% level, respectively.

	Marginal effects for regression model			
Independent variable	I	II	III	IV
Panel A: Reference group is Female & Male loan officer				
Female & Female loan officer	0.025	-0.006	-0.029	-0.020
Male & Female loan officer	0.025	-0.001	-0.031	-0.031
Male & Male loan officer	0.005	-0.007	-0.001	0.007
Duration relationship			-0.002	-0.004**
Any previous application rejected			-0.101***	-0.082***
Any previous loan defaulted			-0.156***	-0.128***
Loan applications per loan officer	-0.083	-0.044	-0.054*	-0.073**
Age of loan officer	-0.004	-0.005*	-0.003	-0.007**
Age of borrower	0.000	0.000	0.001**	0.001***
Civil status	-0.019		0.006	
Self employed	0.030		0.010	
Number persons household	0.016***		0.004*	
Phone availability	0.087***		0.084***	
Borrower lives in Tirana	-0.020		-0.003	
ln(applied amount)	-0.024**	-0.015**	-0.012**	-0.008**
Personal guarantee	0.089***	0.051***	0.058**	0.026**
Mortgage guarantee	0.170***	0.097***	0.068***	0.070***
Chattel guarantee	0.810***	0.741***	0.787***	0.683***
Panel B: Reference group is Male & Male loan officer				
Male & Female loan officer	0.020	0.006	-0.030	-0.039**
Observations	9,885	17,882	8,073	15,874
Adjusted McFadden R-square	0.550	0.520	0.495	0.436
Share of approvals correctly predicted	96.2	93.4	91.7	86.1
Share of non-approvals correctly predicted	77.0	74.1	77.0	77.8

Table 7: Default probability and loan officers' gender – interaction with experience

This table contains the marginal effects of the outcome test with the gender of borrowers and loan officers together with interactions with loan officer experience. All three regression models are based on the sub sample of 6,775 first loans, corresponding to the baseline regression of column 2 in Table 3. They are at the same time first and last loans per borrower. The dependent variable is the occurrence of a borrower being in arrears for more than 30 days during the lifetime of her loan. In addition to the already used independent variables described in Table 3 we interact *Female & Female loan officer* with the loan officer's experience that is proxied by (I) the number of loan applications handled by the respective loan officer until a certain loan was granted; (II) the time since the loan officer works for the bank; (III) the age of the loan officer at the time of the loan approval. To test whether the performance differences depend on loan officer experience we use interactions with two experience dummies (below the median = low experience, above the median = high experience) for each experience proxy. Results for most control variables are omitted. In Panel A, the combination *Female & Male loan officer & low (high) Experience* serves as the reference group, in Panel B, the combination *Male & Male loan officer & low (high) Experience* serves as the reference group. Standard errors are clustered at the loan officer level. All results remain if we use Huber-White standard errors instead. *,**,*** indicate significance at the 10%, 5% and 1% level, respectively.

	Marginal effects for regression model		
Independent variable	I	II	III
Panel A: Reference group is Female & Male loan officer & k Experience			
Female & Female loan officer & Low Experience	-0.048**	-0.067***	-0.045**
Female & Female loan officer & High Experience	-0.044**	-0.028	-0.048***
Loan applications per loan officer	0.010		0.019
Age of loan officer	-0.008***	-0.008***	-0.009**
Time since first loan application		-0.010	
Panel B: Reference group is Male & Male loan officer & k Experience			
Male & Female loan officer & Low Experience	-0.019	-0.043**	-0.021
Male & Female loan officer & High Experience	-0.082***	-0.047**	-0.068***
Observations	6,775	6,775	6,775
Adjusted McFadden R-square	0.116	0.114	0.115
Share of default correctly predicted	73.9	74.5	74.8
Share of non-default correctly predicted	62.0	61.9	61.5

Table 8: Test for differences in workload of female and male loan officers

This table contains the results of a test for differences in the workload of female and male loan officers. We measure the workload in terms of the handled loan applications (columns 1 to 3) and approved loans (columns 4 to 6) by male respectively female loan officers in different time intervals. For example, male loan officers handled 19 loan applications in their first year at the bank whereas female loan officers processed 18.4 loan applications. The comparison is based on all loans in the sample, regardless of whether any information for the control variables used in the other analyses was available or not. We restrict the analysis to the 141 loan officers included in the baseline regression of column 2 in Table 3. *,**,*** indicate significance of a standard t-test for differences between the workloads at the 10%, 5% and 1% level, respectively.

Time a loan officer	Average number of loan applications			Average number of approved loans		
works for the bank	Male loan officer	Female loan officer	Difference	Male loan officer	Female loan officer	Difference
Up to 1 year	19.0	18.4	0.6	14.8	13.8	1.0
Up to 2 years	71.9	71.1	0.8	59.0	52.2	6.8
Up to 3 years	148.5	155.6	-7.1	122.4	117.3	5.2
Up to 4 years	242.8	230.0	12.9	195.0	172.4	22.6
Up to 5 years	288.6	269.2	19.5	226.1	197.6	28.5
Up to 6 years	292.8	283.1	9.7	228.1	205.6	22.4